Journal of Environmental Planning and Management

ISSN: 0964-0568 (Print) 1360-0559 (Online) Journal homepage: http://www.tandfonline.com/loi/cjep20

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Journal of Environmental Planning and Management, 2015
http://dx.doi.org/10.1080/09640568.2015.1017042

The Great Recession or progressive energy policies? Explaining the decline in US greenhouse gas emissions forecasts

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(*Received 9 May 2014; final version received 4 February 2015*)

This paper evaluates the causes of the 23% decline in 2030 US greenhouse gas emissions forecasts between 2007 and 2011. Dynamic regression modeling predicts that the Great Recession contributed to about 67% of the 2008−2009 emissions decline, but then fell to about an 18% share for the 2030 emissions forecast. An analysis of electricity generation forecasts show that switching from coal to gas contributed only 6% to the total 2030 decline. In contrast, regulatory impact assessments and policy analysis showed that state and federal policies were responsible for 46% of the 2030 decline in emissions.

Keywords: regulatory impact analysis; economic growth; greenhouse gas emissions; energy forecasting; United States

1. Introduction

The Unites States is the second largest emitter of greenhouse gases (GHGs) in the world. Energy sector GHG emissions (excluding forestry and non-carbon dioxide gases) were over 6 billion tons in 2012. The residential and commercial sector GHG emissions accounted for about 20% each, industry about 27%, and transportation about 33% of emissions. However, the US Environmental Protection Agency (EPA) announced that US GHG emissions declined in 2012 to 10% below 2005 levels (EPA 2014). The conventional wisdom has been that the decline in actual GHG emissions between 2007 and 2012 has been largely due to the effects of the Great Recession and less coal generation in the electricity sector (Larson 2012; EPA 2014; Lu, Salovarra, and McElroy 2012). While historical emissions are important, energy and GHG forecasts are what drive environmental planning and energy market investment decisions, so it is important to be able to estimate changes in emissions due to business cycle fluctuations, long-term structural changes, and the effects of policy actions. Robust analyses of these dramatic changes in energy and environmental forecasts have been sorely lacking.

Long-term forecasts of US carbon dioxide emissions, as developed by the Annual Energy Outlook (AEO) series of reports using the National Emissions Modeling System (NEMS), have been declining every year for more than half a decade. Table 1 shows a comparison of AEO emissions projections and supply and demand variables that suggest that a number of additional factors have come into play besides the Great Recession between the AEO 2011 and AEO 2007. While GDP fell by only 10%, forecasted GHGs

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Table 1. Percent change in 2030 forecast between AEO 2007 and AEO 2011 reference cases (negative values indicate a decline in 2011 forecast relative to 2007).

Variable	*2030*	*Demand*	*2030*
GHGs	−23%	GDP ($2005)	−10%
Prices		Industrial shipments/GDP	−7%
Crude oil	87%	Commercial demand	−14%
Natural gas	−12%	Residential demand	−17%
Coal	23%	Industrial demand	−8%
Supply		Transport demand	−22%
Total energy supply	−15%	*Energy intensity metrics*	
Coal	−31%	Commercial (kBTU/ft^2)	−12%
Liquid fuels	−22%	Residential (kBTU/ft^2)	−10%
Natural gas	−1%	Industrial (kBTU/$)	1%
Nuclear	−2%	New commercial truck (MPG)	3%
Renewable electricity	29%	New LDV (MPG)	23%
Renewable fuels	169%		
		Electricity sector	
Coal-fired generation	−36%	Petroleum-fired generation	−58%
Natural gas-fired generation	24%	Renewables generation	35%
Nuclear generation	−2%		

Note: GHG = greenhouse gases, GDP = gross domestic product, kBTU = thousand British thermal units, MPG = miles per gallon, LDV = light duty vehicle.

drop by nearly a quarter, and demand for coal drops by almost a third in 2030. This is, partly, due to the fact that coal prices in more recent forecasts were substantially higher, and natural gas prices were slightly lower, than in previous forecasts. The 2011 forecast also included large increases in the use of renewable energy sources by 2030.

Figure 1 shows annual forecasts for GHG emissions and GDP, our primary variables, between the 2007 and 2011 AEO reference case projections for the 2007−2030 period. GHG emissions dip markedly in 2008−2010 in the AEO 2011 data (which is mostly historical data in the NEMS model), then resume an upward trend, but at a substantially

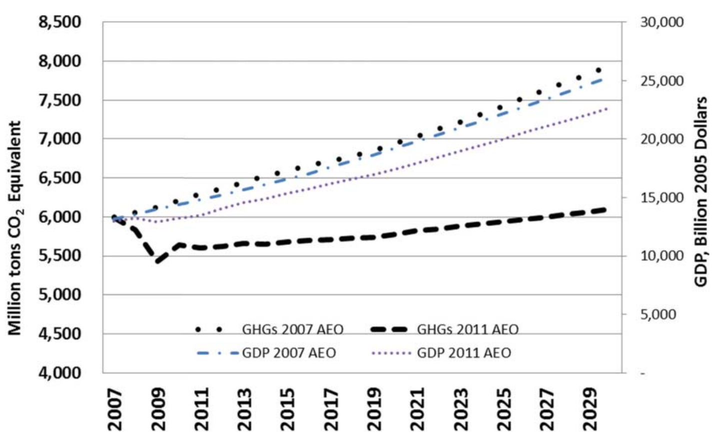


Figure 1. Comparisons of US GHGs versus GDP between AEO 2007 and 2011.

lower growth rate (an average of 0.45% annually over 2011−2030) than in the AEO 2007 forecast (1.24% annually). By contrast, the average GDP growth rates in the two forecasts are only modestly different (2.78%/year in AEO 2011, versus 2.86%/year in AEO 2007). Thus, the main difference in the economic projections underlying the two AEO forecasts is the inclusion of the Great Recession in the AEO 2009−2011 forecasts, which essentially displaces GDP downwards by the equivalent of more than three years' "normal" GDP growth for the entire forecast period.

The goal for this paper is two-fold. First, to estimate the unique impacts of declining economic output on GHG emissions, we use econometric methods that control for other relevant factors. We also estimate the changing impacts of GDP over time. Second, we estimate the GHG impacts of major state and federal policies that were enacted over 2008−2011. To achieve these goals, the next section reviews the relevant literature on energy forecasting and the relationship between GHGs and GDP. Section 3 describes our methods and data. Section 4 presents the regression modeling and policy analysis results. Section 5 discusses the limitations of the analysis and Section 6 presents implications and conclusions.

2. A review of the relevant literature

The first step in informing the forecast decomposition was a selection of the critical variables that have explained past biases between actual energy consumption and Energy Information Administration (EIA) forecasts. Since 1996, the US EIA performs annual retrospective reviews that evaluate the sources of error in its own forecasts compared to realized energy outcomes. EIA (2010) notes, "The underlying reasons for deviations... tended to be the same from one evaluation to the next." Important sources of historical forecasting errors were:

(1) Overestimating the growth rate of GDP,
(2) Errors in fossil fuel price forecasts,
(3) Overestimating energy intensity (5−6),
(4) Errors from not anticipating the effects of regulatory policy change.

The first three sources of error in past EIA analyses are explicitly included in our regression modeling in Section 3. The effects of policy changes are the goal of our regulatory analysis in Section 4.

The next step was a review of energy and GHG decomposition modeling in the economics and statistics literature. This informed our econometric estimation technique discussed below, as well as the variables we used in the model to assess the relationship between GDP and GHG emissions in the AEO data. The existing research that is closest to ours is Lady (2010) who uses regression analysis to evaluate the effects of how changes in assumptions of the NEMS models affects residential and commercial energy outcomes. The empirical research typically shows a positive and significant relationship between energy and/or GHG emissions and economic growth (Apergis and Payne 2010; Apergis *et al.* 2010; Huntington 2007). Other econometric analyses of economy-wide or sectoral energy demand show mixed support for a direct link between GHG emissions, or GDP growth, and low carbon sources of energy (Marrero 2010). Marques and Fuinhas (2011) did not find any evidence of the switch of traditional sources to renewable ones as a result of social responsibility associated with climate change and CO_2 emissions. Sadorsky (2009) used panel co-integration estimates to show that, in the long term, increases in real GDP per capita and CO_2 per capita were major drivers behind per capita renewable energy consumption.

A final strand of research was used to inform the modeling around the structure of the economy and GHG emissions. Authors have used both index decomposition methods and input–output structural decomposition techniques to assess environmental outcomes (Rose and Casler 1996; Ang 2007). For example, Casler and Rose (1998) investigated the sources of change in CO_2 emissions to show the effect of substitution within the energy sector and between energy and other inputs as the leading causes of the decline in carbon dioxide emissions. Also Ebohon and Ikeme (2006) tested for dynamic changes in CO_2 emission intensity and energy intensity effects for two groups of countries. Zhou, Ang, and Han (2010) showed that the total factor carbon emission performance of the countries as a whole improved by 24% over the period and this was mainly driven by technological progress.

3. Materials and methods

The US EIA publishes official energy statistics; therefore, we extracted our data from each reference case in the AEO. The AEO is the official US government energy forecast, and the NEMS model that generates the AEO has been extensively peer-reviewed over the last several decades. The data for our regression analysis include calendar year 2007−2030 forecasts from the AEO reference cases that were prepared over the five years beginning in 2007 and ending in 2011. The full dataset contains $N = 120$ and comes from the five AEOs between 2007 and 2011, where each AEO panel contributes 24 periods between 2007 and 2030. Our analysis begins with the 2007 AEO rather than earlier versions, so that the forecast periods match up (through 2030) and so that the use of (identical) historical data in each of the regression panels (AEO reports) is limited. Each year AEO represents an individual "panel" in the regression models. The natural log of all variables was used to show elasticities and reduce non-linearity in the AEO data. A constant of 1 was added to both sides of the regression equation (GHGs and explanatory variables) prior to the log transformation, in order to maintain the correct sign of each variable as some variables were not significantly different from zero (Hamilton 2006, 128).

Following Marrero (2010) and Marques and Fuinhas (2011), we developed an autoregressive distribute lag (ADL) regression model to predict GHG emissions that includes a lagged value of GHG emissions as well as GDP. ADL models have a long history in energy analysis (Bentzen and Engsted 2001). This dynamic panel data estimation technique assumes that GHG emissions and GDP converge to a state of equilibrium over time.

We use fixed effects in the ADL model to allow heterogeneity across panel units and confine that heterogeneity to the intercept term, which is estimated for each panel. Each panel (or fixed effect) represents a separate AEO year (2007 through 2011). Beck and Katz (2009) argue for the appropriateness of fixed effects models with lagged dependent variables when panels have 20 or more time periods (this analysis has $T = 24$ time periods). The use of fixed effects and lagged dependent variables will have little downward (Hurwicz) bias for the lagged dependent variable (Nickell 1981). Fixed effects models have one major advantage over other estimation techniques that is important here. The fixed effect model controls for all possible characteristics of each panel, thereby reducing the risk of omitted variable bias in the research design (Allison 2005).

Violations of econometric assumptions were carefully tested that might affect our inferences. Serial correlation occurs when the error terms in cases/observations are not independently distributed (trended). Because the data are generated from the NEMS model forecasts, it is highly trended (nonrandom). To mitigate serial correlation, the lagged values of GHG emissions and GDP were included in all ADL models. A test was performed that indicated that the model's error terms were independent of its lagged values and all other variables, and that serial correlation was not significant. Wooldridge (2010) states that it is valid to use fixed effects models in the absence of significant serial correlation (286).

Heteroskedasticity, or non-constant variance in the data, was controlled for with Huber/White/sandwich estimators. We used two-way cluster-robust standard errors as proposed by Cameron, Gelbach, and Miller (2006). These errors are robust to arbitrary within-group correlation clustered on AEO forecasts, and robust to arbitrary contemporaneous cross-panel correlation clustered on year. Multicolinearity, or when the predictor variables in a regression are highly correlated, is an issue in all models that contain lagged values, as they are highly correlated with the current data. Ordinary least squares (OLS) will still generate unbiased estimators in the presence of multicolinearity, but can increase variance, and covariances may potentially lead to rejecting otherwise significant variables. As a robustness test, the models were also estimated with differenced energy price data and the results were largely similar (not shown), giving us confidence in the models' robustness with regard to multicolinearity. A variance inflation test was performed with results below 5, indicating no significant problem with multicolinearity.

3.1. Economy-wide regression model

Our overall goal for the regression analysis was to identify GHG emissions impacts resulting from changes in forecasts of economic activity while controlling for other relevant factors. We are also interested in how the impact of GDP changes over time. The economy-wide supply and demand model that resulted includes GDP as a measure of energy demand, real fossil fuel prices, and primary energy supply shares for fossil fuels, nuclear power, and renewable energy sources, as well as sectoral demand shares (residential, commercial, industrial, and transport).

We selected these variables based on our review of the EIA retrospective analyses and the energy econometrics literature detailed in Section 2. Following the methods of Casler and Rose (1998), we also included a measure of the industrial share of the economy to control for changes in the energy demand mix caused by shifts in economic structure. The equation for the economy-wide model is

$$\begin{aligned} \mathrm{GHG} = {} & \beta_0 + \beta_1 \mathrm{GHG}_{t-1} + \beta_2 \mathrm{GDP} + \beta_3 \mathrm{GDP}_{t-1} + \beta_4 \tfrac{\mathrm{Ind}}{\mathrm{GDP}} + \beta_5 \mathrm{oil} + \beta_6 \mathrm{NG} + \beta_7 \mathrm{coal} \\ & + \beta_8 \mathrm{fuels\%} + \beta_9 \mathrm{NG\%} + \beta_{10} \mathrm{nuclear\ \%} + \beta_{11} \mathrm{renewable\ \%} + \beta_{12} \mathrm{commercial\ \%} \\ & + \beta_{13} \mathrm{residential\ \%} + \beta_{14} \mathrm{tranport\ \%} + \varepsilon, \end{aligned} \tag{1}$$

where GHG = greenhouse gas emissions (million metric tons) carbon dioxide equivalents, GDP = gross domestic product (billions of chained 2005 dollars), Ind/GDP = industrial shipments/GDP, oil = crude oil price in US dollars, NG = natural gas price in US dollars, coal = coal price in US dollars, fuels% = liquid fuel supply share of total energy supply, NG% = natural gas supply share of total energy supply, nuclear% = nuclear energy share of total energy supply, renewables% = renewable energy share of total energy supply, commercial% = commercial energy demand as share of total demand, residential% = residential energy demand share of total demand, transport% = transportation energy demand share of total demand, ε = stochastic error term.

3.2. Sectoral regression models

In this section, we increase the resolution of the econometric model by examining the energy-consuming sectors instead of pooling them all together in the economy-wide model. This analysis identifies variables that are substantive and significant at the sector level but not at the aggregate level.

In the buildings and industry model, we drop primary energy supply share variables and instead focus on the supply shares (by energy source) in electricity generation, which has been considerably revised between the 2007 and 2011 versions of the AEO forecasts. We also include sectoral energy intensity metrics to investigate increased energy efficiency in delivering energy services such as heating, cooling, lighting, and industrial process energy. The equation for the buildings and industry model is

$$\begin{aligned}\mathrm{GHG} = \beta_0 + \beta_1\mathrm{GHG}_{t-1} + \beta_1\mathrm{GDP} + \beta_3\mathrm{GDP}_{t-1} + \beta_4\tfrac{\mathrm{Ind}}{\mathrm{GDP}} + \beta_5\mathrm{oil} + \beta_6\mathrm{NG} + \beta_7\mathrm{coal}\\ + \beta_8\mathrm{NG\ gen\%} + \beta_9\mathrm{renewable\ gen\%} + \beta_{10}\mathrm{nuclear\ gen\,\%} + \beta_{11}\mathrm{residential}\\ + \beta_{12}\mathrm{commercial} + \beta_{13}\mathrm{industrial\,\%} + \varepsilon,\end{aligned} \tag{2}$$

where GHG = greenhouse gas emissions (million metric tons) carbon dioxide equivalents, GDP = gross domestic product (billions of chained 2005 dollars), Ind/GDP = industrial shipments/GDP, Oil = crude oil price in US dollars, NG = natural gas price in US dollars, Coal = coal price, NG gen% = natural gas supply share of total electricity generation, renewable gen% = renewable energy supply share of total electricity generation, nuclear gen% = nuclear energy share of total energy electricity generation, residential = residential energy intensity (kBTU/ft^2), commercial = commercial energy intensity (kBTU/ft^2), industrial = industrial energy intensity (kBTU/\$ shipments), ε = stochastic error term.The equation for the transport model is:

$$\begin{aligned}\mathrm{GHG} = \beta_0 + \beta_1\mathrm{GHG}_{t-1} + \beta_2\mathrm{GDP} + \beta_3\mathrm{GDP}_{t-1} + \beta_4\frac{\mathrm{Ind}}{\mathrm{GDP}} + \beta_5\mathrm{oil}\\ + \beta_6\mathrm{RFS\,\%} + \beta_7\mathrm{LDV} + \beta_8\mathrm{truck} + \varepsilon,\end{aligned} \tag{3}$$

where GHG = greenhouse gas emissions (million metric tons) carbon dioxide equivalents, GDP = gross domestic product (billions of chained 2005 dollars), Ind/GDP = industrial shipments/GDP, oil = crude oil price, RFS% = federal renewable fuel standard requirement, LDV = light duty vehicle miles per gallon (MPG) standard, truck = commercial truck MPG standard, ε = stochastic error term.

4. Results

Our results are split into two sections: regression results and the policy analysis results. The AEO reference case forecasts for year 2030 GDP declined by only 10% between the 2007 and 2011 forecasts, as shown in Figure 1. Regression analysis was used as described above to estimate how much of the forecasted change in GHG emissions in the reference case AEO 2007 and 2011 forecasts can be attributed to the impacts of the Great Recession and to (slightly) slower subsequent economic growth assumptions. The AEO projected growth rate in GDP is a trend projection, that does not account for business cycles. The regression results allow us to estimate the effects of declining economic activity on GHG emissions, controlling for associated changes in the GHG intensity of electricity generation sources. As robustness tests, we also examine the effects of GDP on GHGs in the short term (2007–2020), and without prices in the ADL model.

Table 2 shows the regression results. The log–log model shows the percent change in GHGs for a one percent change in the predictor variables. The coefficient of

Table 2. Economy-wide regression results for GHG emissions.

Variables (logged)	Base model 2007–2030	Alternate A 2007–2020	Alternate B No prices
Lagged GHGs	0.67^{***}	0.50^{**}	0.75^{***}
	(0.000)	(0.016)	(0.000)
GDP	0.94^{**}	0.88^{***}	0.92^{**}
	(0.017)	(0.009)	(0.026)
Lagged GDP	-0.81^{**}	-0.73^{***}	-0.83^{**}
	(0.024)	(0.007)	(0.032)
Industrial shipments/GDP	−0.04	0.12	-0.11^{*}
	(0.601)	(0.615)	(0.093)
Crude oil price	−0.02	−0.04	
	(0.294)	(0.174)	
Natural gas price	−0.00	0.02	
	(0.987)	(0.199)	
Coal price	-0.07^{*}	−0.19	
	(0.095)	(0.174)	
Liquid fuels supply (%)	0.31	−0.24	0.41^{***}
	(0.120)	(0.134)	(0.004)
Natural gas supply (%)	-0.41^{***}	0.31	-0.35^{***}
	(0.004)	(0.133)	(0.008)
Nuclear supply (%)	−0.44	−0.35	−0.01
	(0.100)	(0.639)	(0.842)
Renewables supply (%)	-0.88^{*}	−0.72	-0.82^{**}
	(0.052)	(0.120)	(0.046)
Commercial energy demand (%)	−0.33	−0.28	−0.11
	(0.191)	(0.267)	(0.612)
Residential energy demand (%)	0.34	0.39	0.27
	(0.574)	(0.518)	(0.517)
Transportation energy demand (%)	−0.05	−0.26	−0.03
	(0.883)	(0.615)	(0.905)
Constant	1.86^{***}	3.20^{***}	1.31^{***}
	(0.005)	(0.007)	(0.004)
Observations	118	68	118
R-squared	0.990	0.962	0.988
Number of AEO years	5	5	5
Fixed effects	Yes	Yes	Yes

Notes: Robust p-values in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
The full dataset that contains $N = 120$ comes from the five AEOs between 2007 and 2011, where each AEO panel contributes 24 periods between 2007 and 2030. The regression results in Tables 2 and 4 show 118 observations, as the 2007 observations from the 2010 and 2011 AEO forecasts are dropped. Alternative A in Table 2 shows 68 observations because of the shorter time period: $14 \times 5 - 2 = 68$.

determination (R^2) for the base ADL model explains over 99% of the variation in GHG emissions, which is expected with the lagged values of GHGs and GDP in the model as explanatory variables. The F-statistics (not shown) indicate that the combined effects of the explanatory variables are statistically different from zero.

National income (using GDP as a proxy) is used as an indicator of total energy demand. Energy demand in the AEO that leads to GHGs is parameterized in the models by GDP that includes industrial production, housing starts, and commercial building floor space. Recall that the goal of the regression modeling is to partition out the change in GHGs that is explained by lower GDP, while controlling for price and supply variables in the AEO forecasts. Following the methods of Sadorsky (2009) and Marques and Fuinhas (2011), fossil fuel prices are included in the base analysis. Our results indicate that higher coal prices are weakly related to lower GHG emissions. On the energy supply side, higher renewable energy and natural gas shares of primary energy supply were identified as statistically significant predictors of reduced GHG emissions. The negative coefficient for renewable energy supply is the largest of the supply variables, indicating the larger GHG reductions from implementation of renewable energy as compared to nuclear energy and natural gas.

The primary energy supply shares in Table 2 use coal as a base category in the model. This means that coal supply share was excluded to avoid perfect correlation between the variables and the other variables can be interpreted relative to coal. The reason that the nuclear supply share was not significant is likely due to the lack of variation in nuclear supply over the forecast period; the AEO forecast includes very limited changes in nuclear generation. Appendix 1 shows the descriptive statistics for the data and indicates that there is very limited variance in the fuel and sector share forecasts in the AEO reference cases. This is one potential explanation for the lack of significance for these important variables, and needs to be further examined in future research that decomposes energy forecasts.

On the demand side, the sectoral variables used industrial demand as a base category. As a result, an increase in commercial and transport demand relative to industrial demand predicts reductions in GHG emissions, but none of the effects were significant from zero.

Across a range of econometric estimations, the most consistent predictor of higher GHG emissions on the demand side was GDP. Economy-wide demand for energy services is a function of economic activity and income. Lower incomes reduce demand for electricity for appliances, for gas and electricity used for building heating and cooling, for diesel fuel used for mining and construction, for gasoline and other fuels powering vehicle travel, and for many other uses of energy throughout the economy. For example, in the building sector, growth in housing and commercial floor space is in large part a function of income (measured as GDP) and population growth, so using GDP as an explanatory variable should capture the majority of variance in demand growth between forecasts.

The econometric methodology described above generates predictions of the unique contribution of changes in GDP in the model toward changes in GHG emissions, controlling for the effects of the other variables. The short-run (immediate) effect of a one percent (1.0%) decline in GDP results in a 0.94% decline in GHG emissions. For example, the 2.6% decline in 2008 GDP forecasts between the 2007 and 2011 AEO reports explains about 66% of the 3.7% decline in GHGs $[(0.94 \times 2.6) = 2.4)/3.7]$.

The long-run effect of GDP on GHG emissions can be calculated from the coefficients of lagged GHG emissions, GDP, and lagged GDP, and is estimated by $\frac{\beta_0+\beta_1}{1-\varphi}x$, where $\beta_0 = \text{GDPt}$; $\beta_1 = \text{GDP}_{t-1}$, and φ is the lagged GHG coefficient. In this case, the long-run equilibrium is equal to (0.94−0.82)/(1−0.67) = 0.36 or 36%. Put another way, the 10% decline in 2030 GDP forecasts between the 2007 and 2011 AEO forecasts is predicted to result in a ~4% decline in GHG emissions. Instead, GHG emissions declined by 23%, meaning that multiple other factors are required to explain the long-term GHG decline.

When the long-run equilibrium is disturbed during a recession, the rate of correction for the GHGs and GDP back to their equilibrium can be estimated as (1 − lagged GHG emissions coefficient). Assuming a lagged GHG coefficient of 0.67% means that the speed of adjustment is relatively slow at 0.33% per year. We calculated each year's GDP coefficient based on the model's impulse-response function for each year following the beginning of the recession in 2008 to better estimate the effect of GDP on GHGs. For each year following 2008, the response function was estimated as $\varphi(t-1) \times (\beta_1 + \varphi\beta_0)$ and was subtracted from the prior year's coefficient. By 2010, about half of the adjustment to the long-term equilibrium had occurred. Table 3 shows the estimated GDP coefficient for selected years.

Part of the explanation is because the short-run (immediate) relationship between GDP and GHG emissions (0.94% from Base model in Table 3) is over two times greater than the long-run multiplier of 0.36. The short-term effect of GDP is larger than long-term effect because of long-term declines in the energy intensity of the economy, which in turn is due to autonomous energy efficiency improvements and/or structural changes in the economy away from energy-intensive sectors (Webster, Paltsev, and Reilly 2008).

The 0.36 long-run GHG income elasticity calculated above is related to the energy income elasticity. The GHG elasticity estimate is lower than historical income elasticities for the US and OECD countries which have been estimated between 0.57 and 0.64, respectively (Mahadevan and Asafu-Adjaye 2007; Gately and Huntington 2002). However, energy income elasticities do not account for changes in GHG intensity, such as switching from coal to gas or renewable energy sources, which, as we discuss below, contribute significantly to US GHG reductions in the NEMS model's forecasts.

Using different starting and ending dates for the analysis did change the GDP coefficients substantively. Alternate A in Table 2 shows only the period of the recession and its aftermath (2007−2020). The GDP short-term coefficient was reduced to 0.88% while the long-run effect declined to 0.30%, which was derived as ((0.88−0.73)/(1−0.50)). We also tested the effects of GDP on GHG emissions in the economy-wide model without prices, as shown in Alternate B in Table 2. This more parsimonious model specification eliminates concerns that energy prices are endogenous to supply and demand variables (and GHGs), and shows that without price variables the effects of GDP are slightly lower at 0.36, derived as ((0.92−0.83)/(1−0.75)). This model does predict significantly lower GHG emissions with higher natural gas and renewables supply shares. Conversely, a higher liquid fuel share is predicted to result in higher GHG emissions.[1] The commercial, residential, and transportation demand shares are not significant. In an unreported regression, we trimmed the Base model to exclude the demand shares. The results were largely unchanged from the Base model results in Table 2.

Table 3. GDP coefficient over time.

	2008	2009	2010	2015	2020	2030
% Δ in GHGs for 1% Δ in GDP	0.940	0.760	0.639	0.427	0.398	0.394

4.1. Sectoral results

These economy-wide results allowed us to further refine our analysis at the sectoral level for buildings (residential and commercial/institutional sectors) and industry as well as for transportation. Table 4 shows that the short-run relationship between GDP and GHG

Table 4. Sectoral regression results (2007−2030).

Variables (logged)	Buildings and industry	Transport
Lagged GHGs	0.15	0.60***
	(0.182)	(0.000)
GDP	0.93***	0.86***
	(0.001)	(0.001)
Lagged GDP	−0.44***	−0.64***
	(0.005)	(0.001)
Industrial shipments/GDP	0.40***	0.21
	(0.001)	(0.171)
Crude oil price	−0.00	−0.04**
	(0.649)	(0.025)
Natural gas price	−0.01	
	(0.386)	
Coal price	0.03	
	(0.476)	
Natural gas generation (%)	−0.36***	
	(0.007)	
Renewables generation (%)	−0.58***	
	(0.007)	
Nuclear generation (%)	−0.65***	
	(0.009)	
Residential energy intensity (kBTU/ft^2)	0.37***	
	(0.007)	
Commercial energy intensity (kBTU/ft^2)	0.12	
	(0.198)	
Industrial energy intensity (kBTU/$ shipments)	0.20***	
	(0.000)	
Renewable fuels (%)		−0.36***
		(0.003)
Light duty vehicle (MPG)		−0.00***
		(0.006)
Commercial truck (MPG)		0.00
		(0.768)
Constant	0.15	1.11***
	(0.780)	(0.002)
Observations	118	118
R-squared	0.99	0.99
Number of AEO years	5	5
Fixed effects	Yes	Yes

Notes: Robust *p*-values in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

emissions is largely unchanged from the results found in the economy-wide model (0.94) compared to the Buildings and Industry model (0.93) and slightly lower in the Transport model (0.86).

The sectoral models show the robustness of GDP coefficient estimated in previous models. The industrial share of GDP is marginally significant, with a much larger coefficient for buildings and industry. Higher natural gas and coal prices predict lower GHG emissions in the buildings and industry sectors. We find evidence that fuel switching away from coal in the electricity sector is also an important source of GHG emissions reductions. We estimate the impacts of higher relative coal prices in the electricity generation sector in our fuel switching analysis below. Finally, two of the end-use intensity measures are significant, with residential energy intensity having a much larger effect on GHG emissions than industrial intensity.

In the transportation model in Table 4, higher crude oil prices predict lower GHG emissions, as does a greater share of renewable fuel use. However, outside of the transportation sector, we found little effect on GHG emissions from higher oil prices while controlling for demand reductions from lower GDP (Table 3). This result is consistent with other recent energy studies (Sadorsky 2009). Light-duty vehicle efficiency (MPG) requirements are associated with reduced GHG emissions, while commercial truck MPG requirements are not.

Table 3 summarizes the first goal of this paper, and shows that the relationship between GDP and GHG is large right after the Great Recession, but declines over the long term in the AEO forecasts.

4.2. Policy analysis results

Recall from Section 4 above that the 10% decline in 2030 GDP forecasts between the 2007 and 2011 AEO forecasts is predicted to result in a ~4% decline in GHG emissions. Instead, GHG emissions declined by 23%, meaning that multiple other factors are required to explain the long-term GHG decline. As a result, we turn to the second objective of the paper. Recall from Section 2 that one of the consistent sources of errors in AEO forecasts were regulatory policies. We employ policy analytical methods to measure what else is going on in the AEO forecasts that might plausibly explain the balance of the GHG declines. The effects of major federal and state policy actions that occurred between 2008 and 2011 were analyzed using the results of existing studies, or were calculated exogenously based on AEO data or other data sources. The EIA rarely provides comparative static analyses of the effects of major legislation on reference case projections, with the exception of the AEO's explicit consideration of the impacts of the American Recovery and Reinvestment Act (ARRA 2009). As a result, external analyses from the EIA, the US EPA, and other studies, as well as our own analysis of EIA data, were used to estimate GHG impacts.

We use policy analysis to assess the effects of various policy and market factors in explaining GHG emissions: electricity generation, building energy intensity, industrial energy efficiency, as well as transportation policies. The effects of the policy and market variables were included (1) because they were explicitly modeled in the AEO reference cases within the NEMS model, (2) because they are typically included in the energy economics literature as described above (Marques and Fuinhas 2011; Marrero 2010; Ang 2007; Huntington 2007; Casler and Rose 1998) or (3) because they have been selected by the EIA (2011) as important sources of forecasting error in previous versions of the AEO. To reduce the risk of double-counting GHG reductions, we purposefully modeled the

GHG impacts taking into account the lower future economic activity and GDP growth in the 2011 AEO forecast.

4.2.1. Electricity generation

Forecasted 2030 GHG emissions from the electricity sector fell by 27% between the AEO 2007 and 2011 forecasts. The change is the result of several inter-related factors. Chief among these was lower electricity demand (about 15% lower in 2030 in AEO 2011) resulting from lower economic activity and improvements in energy efficiency. Another key factor was a significant reduction in coal-fired generation due to higher coal prices and lower natural gas prices in the later AEO reference cases. Lower natural gas prices resulted in gas generation replacing coal generation during the 2009 Great Recession (Lu, Salovarra, and McElroy 2012). The NEMS power sector module is a least-cost optimization model, so the interaction between the declines in natural gas prices, along with higher coal prices, results in forecasted fuel switching from coal to gas in the power sector.

4.2.1.1. Electricity generation sector. The electricity generation sector accounts for a substantial fraction of the United States' GHG emissions – a total of 2.4 billion (metric) tons of carbon dioxide (CO_2) as of 2007, more than 40% of national CO_2 emissions in that year. The 2007 version of the AEO reference case shows total electricity sector emissions in 2030 of over 3.3 billion tons of CO_2, while the AEO 2011 forecasts emissions of over 2.4 billion tons. As such, the difference in electricity sector emissions between AEO 2007 and AEO 2011 in 2030 – about 900 million tons – accounts for very close to half of the overall difference in 2030 forecasted emissions.

Here we identify which portions of the differences in CO_2 emissions that appear between the two electricity sector forecasts stem from changes in economic conditions, assumptions about GHG-related policies, and changes from other factors such as changes in relative fuel prices. The decomposition of the drivers of the different electricity sector CO_2 emissions between the two forecasts is made more challenging because of a number of trends which include:

- Demand: 2030 electricity demand fell from 5800 terawatt hours (TWh) to slightly more than 4900 TWh between the 2007 and 2011 forecasts. Key drivers include the impacts on electricity demand in the recession of 2007–2009, reductions in electricity demand as a result of energy efficiency programs and policies, as well as differences in assumptions about naturally occurring improvements in end-use efficiency.
- Coal-to-gas fuel switching: a 35% reduction in the generation of electricity from coal, along with a 24% increase in the generation of electricity from natural gas between 2007 and 2011.
- Coal generation emissions factor (tons CO_2/megawatt hour): there is a decrease over time in the CO_2 emission factor for coal-fired generation, but the trend is quite different in the two forecasts. In AEO 2007, the emission factor declines by about 9% from 2012 to 2030, while in AEO 2011, the emission factor declines by less than 4% over the same period. The reason for this difference is likely that in AEO 2011, a larger fraction of the coal-fired capacity operating in 2030 would be of older, less efficient plants with higher emission rates. In contrast, the AEO 2007 forecast, with its higher levels of coal-fired generation, required the construction of more newer, higher efficiency plants.

- Renewable generation: by 2030, AEO 2011 forecasts 35%, or 184 TWh, more renewable generation than does AEO 2007. This increase can be attributed to the federal production and investment tax credits (in the short term), as well as state policy actions and market forces in the long term. The additional use of renewable electricity generation is estimated to explain a total of just over 7% of the reduction in overall GHG emissions between AEO 2007 and AEO 2011 in both 2020 and 2030.

To separate the effects of state actions from other influences on AEO renewable energy forecasts, we performed an analysis of state Renewable Portfolio Standard (RPS) legislation included in the AEO reference case forecasts. The EIA (2008) posits, "If recent trends continue, the state RPS programs will exert growing influence over the national energy mix." Using EIA reports, we estimated the share of new renewable electricity attributable to state RPS activity as 75% of the additional deployment of renewable generation by 2030. Based on this assumption, about 5.5% of the 7% total reduction from increased renewable energy deployment (above) is estimated to result from state RPS fulfillment, with the balance of 1.5% developed outside the mandates of state RPS programs.

4.2.2. *Building energy intensity*

AEO estimates between 2007 and 2011 of residential and commercial energy intensities (measured as consumption of energy per square foot of building floor space) for 2030 declined by 10% and 12%, respectively. The EIA (2010) notes**,** "Energy intensity has been the concept most often overestimated" (7). The NEMS model assumptions for technological improvements have become more optimistic over the years, and have also started to include an element of efficiency improvement due to learning through experience "in more recent projections" (EIA 2010, 6). We estimate the effects of improved energy intensity in later AEO versions by analyzing the decline in energy consumption per square foot in the building sectors. Some of the improvements in energy intensity are due to endogenous improvements in device efficiencies (for example, ongoing replacement of incandescent bulbs with compact fluorescent lamps, which are three or more times as efficient in producing light from electricity) and some to policy interventions.

The effects of the changes in energy intensities on GHG emissions are estimated as the annual percentage difference in end-use efficiency between the 2007 and 2011 reference cases, multiplied by sectoral 2007 GHG emissions. From this estimate of a difference of about 350 $MTCO_2$ in 2030 between the two forecasts, we subtract the GHG impacts of state and federal efficiency-related policies as estimated below. The EIA (2009a) notes that recent trends in state energy intensity are taken into account in energy projections, so AS to avoid double counting energy and GHG emission reductions, we assume that only half the net intensity difference is due to technological change, or approximately 70 $MTCO_2$ in 2030. The assumption of one half of intensity differences being attributable to technological change is used for lack of an empirical estimate of this parameter.

The effects of the Energy Independence and Security Act (EISA) of 2007 were also included. The energy impacts from EISA were modeled in AEO 2008 and 2009 for the provisions in EISA that established specific tax credits, incentives, and standards. We updated a report from the American Council for an Energy-Efficient Economy (ACEEE

2008) that estimated the electricity and fuel savings from the EISA. We converted the energy savings into GHG using relevant GHG emissions factors. Also, the ACEEE (2008) estimates were updated for this analysis to reflect the lower growth rates in electricity demand since 2008. Based on the revised analysis, we estimate 74 $MTCO_2e$ in GHG reductions in the AEO 2011 forecast, relative to AEO 2007, by 2030 can be attributed to EISA (2007) Title 3 provisions.

The effects of the ARRA were also included. The AEO 2009 analyzed the effects of ARRA. ARRA allocated $3.1 billion for states to implement or enhance energy efficiency programs. In this analysis, we include only weatherization and building efficiency improvements that the EIA estimated reduced heating and cooling consumption by 1.7% and 3.4%, respectively, in 2030. For this analysis, the AEO 2009 estimates of ARRA demand reductions were reduced by an average of about 5%, which reflects the estimated decline in building energy demand between the 2009 and 2011 AEO forecasts.

Because states have primary authority for regulating demand-side management programs, improvements in energy efficiency can be attributed to state policy actions. ACEEE (2011) publishes an analysis of energy efficiency performance standards enacted by the states. This information, along with US state energy data published by EIA (2011), allowed us to estimate the GHG reductions associated with the incremental annual reductions from new electricity and natural gas demand-side management programs. ACEEE (2011) showed a mean electric efficiency target of 0.84% of sales from 28 states with efficiency standards. These targets ranged from 0.10% of sales in Texas to 2.00% of sales in Massachusetts, Illinois, and Rhode Island. Mean gas efficiency targets were considerably lower at 0.50% of sales. We estimated state energy efficiency electricity and natural gas savings of 0.52% and 0.15% of sales nationwide, respectively, assuming that the 28 states represent 61% of electricity sales and 33% of natural gas sales from EIA (2011) energy sales data.

These values were used for all subsequent forecast years, which conservatively assume no expansion of efficiency standards either in policy goals or geographic expansion to states that lacked existing standards as of 2011. To convert electricity savings targets to GHG emissions savings, we assumed an avoided electricity CO_2 intensity of 0.51 tons/MWh through 2015, effectively assuming that energy efficiency here results in reduced generation by peaking natural gas units, and for 2016–2030, we assumed that efficiency investments displace the use of new natural gas combined-cycle combustion turbines with average heat rates of 6800 Btu/kWh, resulting in avoided emissions of 0.36 tons/MWh. These too are relatively conservative assumptions, as energy efficiency will typically displace a mixture of base load and peaking generation, and thus could probably be expected to reduce coal-fired and gas-fired generation, resulting in higher avoided emission factors on average. We assumed an 8% average rate of transmission and distribution losses, which are avoided by energy-efficiency measures applied at the point of electricity end-use.

4.2.3. Industrial energy efficiency

Industrial kBTU/$GDP dropped considerably in the short term (2008–2014) in the 2011 AEO forecast compared to 2007, indicating that the drop was due to a continued move away from energy-intensive manufacturing rather than endogenous efficiency improvements. As a result, we include only GHG reductions associated with energy intensity improvements from buildings and not industrial energy efficiency improvements. The net effect of not including industrial energy intensity improvements equates to these effects being included in the “unattributed” sources.

4.2.4. Transportation policies regulatory impact assessments

Major federal transportation policies are analyzed as transport-related GHGs emissions in 2030 dropped by 26% between the 2007 and 2011 AEO reference case forecasts. Demand reductions contributed to the drop, as forecasts for vehicle miles traveled dropped by 11%. Several significant federal policy actions, however, were enacted over the period, and these help to explain the remainder of the dramatic drop in transport-related GHG emissions forecasts.

The Corporate Average Fuel Economy (CAFÉ) standards for the AEO reference cases were updated several times between 2007 and 2011. EISA (2007) Title 1 for vehicle efficiency standards and credit trading are simulated in the AEO 2008, and modeling of subsequent legislation was updated in AEO 2009 and 2010. The Obama Administration's 2009 CAFÉ standards are primarily included in AEO 2010 modeling. For vehicle model years 2016 through 2020, fuel economy standards are assumed to increase in stringency to achieve 35 MPG on average for the new light-duty vehicle fleet in 2020, after which the standards remain constant. We updated the emissions impacts of federal CAFÉ standards for this analysis as estimated in the EPA's CAFÉ Regulatory Impact Analysis (2010a). The EPA estimated direct annual GHG emissions reductions for the policy of about 15 $MTCO_2$ in 2012, rising to over 273 $MTCO_2$ by 2030. To account for slower economic growth, the effects of CAFÉ standards in the EPA's Impact Analysis were reduced by the percentage difference between projected new vehicle sales in AEO 2011 relative to the 2009 AEO updated reference case, which averaged about 3.4% over the 2008–2030 period. Thus, GHG reductions from enhanced CAFÉ standards between the AEO 2007 and 2011 forecasts are estimated at 130 $MTCO_2$ in 2020 and 270 $MTCO_2$ in 2030.

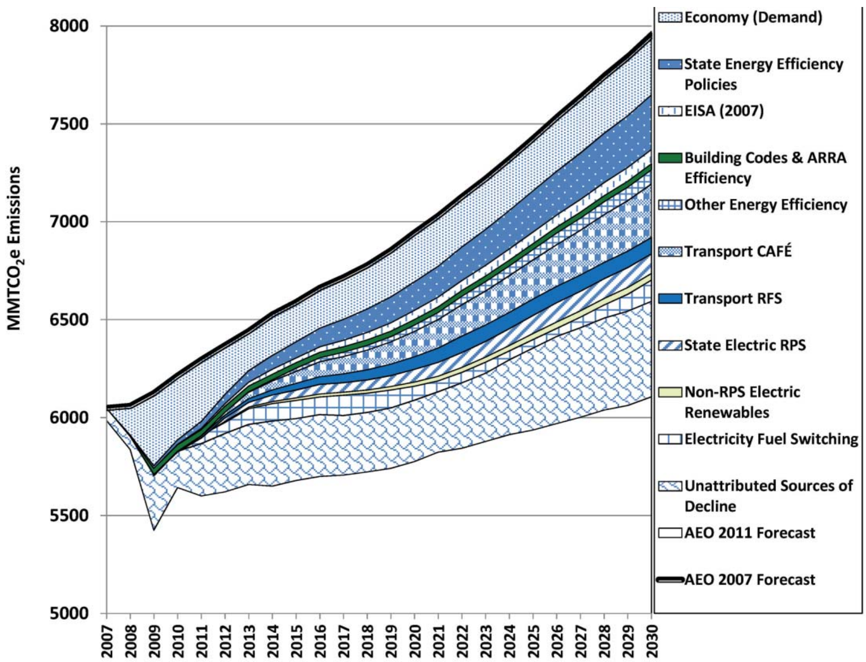
Renewable transportation fuels were also modeled as they were included in the AEO 2008 reference case under EISA (2007) Title 2 and updated in later AEO versions. The impacts of the first renewable fuels standard (RFS1) under EPACT 2005 were included in the AEO 2007 and are thus not modeled as a difference between AEO 2007 and 2011 forecasts. We estimate the impacts of the EISA (2007) and other policy changes to the RFS using the US EPA RFS Regulatory Impact Analysis (2010b). The GHG impacts from the 30.5 billion gallons of renewable transport fuels estimated for 2022 in the EPA Impact Analysis are incremental to the 2007 AEO baseline of 13.05 billion gallons of biofuels. We assume that biodiesel and ethanol incentives under the Energy Improvement and Extension Act of 2008 and other relevant legislation are also subsumed in the EPA renewable fuel share analysis.

Table 5 integrates the GHG reductions MMTCO2e from the policy analysis section with the drop in GHGs predicted from Table 3. To convert the regression results into GHGs, we multiplied the estimated GDP coefficient by the %GDP forecasting error by the 2007 AEO GHG forecast in each year. For example, 2030 GHG emissions attributable to the drop in GDP forecasts, controlling for all other variables in the model including prices, is 18% of the 2007 AEO forecasted emissions for 2030 equal to 323 MMTCO2e ($0.394 \times 0.103 \times 7950$ MMTCO2e). This is larger than the estimated 2030 GHG reductions from state energy efficiency policies at 279 MMTCO2e, and Federal CAFÉ standard reductions of 272 MMTCO2e.

Figure 2 builds on Table 5 by showing a time-series of the effects of the sources of GHG declines over the 2007–2030 period, utilizing the regression results from the Base model in Tables 2 and 3, the results from the regulatory impact analyses, the electricity sector fuel switching analysis, and the energy efficiency policy analyses. The graph is bounded at the top by the 2007 GHG forecast and at the bottom by the 2011 GHG forecast.

Table 5. Contribution of the sources of GHG emissions declines.

Source	2020	2030	Source
Economy (demand)	22%	18%	Tables 2 and 3 for Base model
Electricity fuel switching	6%	6%	Section 4.2.1 and Online Appendix
State electric RPS	6%	5%	Section 4.2.1 and EIA (2008, 2009a)
Non-RPS electric renewables	2%	2%	Section 4.2.1 and US EIA reports
Transport RFS	6%	5%	Section 4.2.4 and EPA (2010b)
Transport CAFÉ	11%	15%	Section 4.2.4 and EPA (2010a)
Building codes and ARRA efficiency	2%	2%	Section 4.4.2 and EIA (2009b)
EISA (2007)	4%	4%	Section 4.4.2 and ACEEE (2008)
State energy efficiency portfolio standards	12%	15%	Section 4.4.2 and ACEEE (2011), EIA (2011)
Autonomous energy efficiency (Buildings)	3%	4%	Section 4.4.2 and Table 4 (buildings)
Unattributed sources of decline	27%	26%	Unattributed reductions from above analyses



* Abbreviations: RPS = Renewable Portfolio Standards, ARRA = American Recovery and Reinvestment Act, EISA = Energy Independence and Security Act (of 2007), CAFÉ = Corporate Average Fuel Economy

Figure 2. Time series of relative contributions to declines in AEO forecasts of US GHG emissions. (See online colour version for full interpretation.)

5. Discussion

Combined, the ADL regression modeling and the policy analysis help to identify the factors that explain why GHG emissions forecasts dropped 23%, but GDP forecasts fell only 10% between 2007 and 2011. Each of the analyses provides a unique part of the picture. However, there are also declines in GHG emissions in the AEO forecasts that we do not ascribe sources to. These unattributed declines are estimated at about 26% of the total decline in 2030. This category includes policy actions and market outcomes in the NEMS reference cases that go beyond the changes in GDP and the policy analysis present above. First, the economy-wide effects of changes in relative prices are difficult to estimate because they integrate supply and demand. The unattributed category includes higher oil prices, which were shown to be important in the transportation sector, but not in economy-wide models. While we do estimate the effects of coal-to-gas fuel switching in the electricity sector, we do not partition out the GHG effects of relative price changes of direct fuel use in the buildings and industrial sectors (Huntington 2007). The unattributed sources of decline in forecasts demonstrate that our analysis is not overly deterministic in that it does not attribute the entire decline in GHG emissions between forecasts to specific sources, and also implies that emission declines have not been double-counted in the analysis.

Airborne emissions control policies covering non-GHG pollutants are not included in the analysis and are thus also in the unattributed category. Other simulations, including EPRI (2012), show that airborne emissions policies (not including CO_2) are likely to cause significant retrofits and retirements of existing coal generation through 2035, which will likely result in large GHG reductions. In sum, though it appears that airborne emissions policies may have contributed to the decline in coal generation forecasts between the 2007 and 2011 AEO reference cases, estimating the magnitude of their impact is difficult outside of the NEMS model and it is not clear how well, or if at all, these policies have been implemented in the AEO forecasts.

Several other policies have been included in AEO reference cases, but we have not separated them out in this decomposition analysis because their impacts on GHG emissions forecasts are small. These include the Regional Greenhouse Gas Initiative as well as California Assembly Bill 32 (AB 32), the Global Warming Solutions Act of 2006. State-level appliance standards were also not analyzed, as they are typically responsible for a much smaller share of energy efficiency savings than federal standards, and are also subsumed in our estimate of other energy efficiency savings. Other policies are not quantified due to a lack of data about how the effects of these policies are included (or not) in the AEO forecasts.

5.1. Limitations of the analysis

With the exception of the estimates for the effects of GDP on GHG emissions, each of the variables attributed to GHG declines in this analysis have been performed on a stand-alone basis. However, there could be some interactions between the policies. For example, energy efficiency improvements can also increase consumption as the cost of energy services declines. This "rebound" effect could cause the energy efficiency variables to overestimate their importance in explaining the decline in GHG emissions, but estimating the rebound effect in forecasts is difficult. Similarly, the effect of combining renewable and energy efficiency policies may result in lower emissions reductions for the combined policies together relative to results indicated by stand-alone analyses, because the renewable policies may not be as effective at reducing GHG emissions under conditions of lower energy demand.

However, we are not concerned about "real-life" rebound effects of effective policies, just whether or not the interactions are accounted for in the NEMS model. If they are, then GHG emission declines are smaller than they would be otherwise. If they are not, then the NEMS model is overstating GHG reductions, but our stand-alone analyses would only be assigning a larger share of reductions to renewables policies.

This last point leads to, perhaps, the most important observation about this analysis, that we are analyzing what the NEMS model estimates are the effects of economic activity, relative prices, and state and federal policies on GHG outcomes, not what has happened historically, nor what the future will likely reveal.

6. Conclusions and policy implications

Although there are many possible approaches that can be used to explain the differences between AEO GHG emissions forecasts of different vintages, the analytical methods described above are straightforward and have a long history of use in energy analysis. We have also compared our regression results across a range of econometric models (incorporating, for example, different variables and AEO results from different time frames) and found the overall findings of the different regression models to be broadly consistent. Our results use secondary data sources where possible to estimate the GHG impacts of national and state policies.

The Great Recession, and slower subsequent economic growth, was the single largest contributor to the 2030 emissions decline. But, the long-term effect of lower GDP was just one of many factors driving the difference between the AEO forecasts. Figure 3 shows that the 46% contribution of end-use energy efficiency policy actions at the state and federal level (including CAFÉ standards) were over twice as important in explaining GHG emissions projections as the change in GDP forecasts in 2030. Relative prices, defined as coal-to-gas fuel switching and non-RPS renewables in the electricity sector, as well as autonomous energy efficiency improvements in the buildings sector, contributed 12% to the 2030 emissions forecast drop. As mentioned above, the unattributed category also includes increases in oil prices as well as coal-to-gas fuel switching in the industrial sector, as well as airborne emissions policies.

It is important to understand the sources of changes in GHG forecasts for their role in planning and management. If energy efficiency policies explain more of the changes in emissions forecasts, then planners know that their policies are having an impact (at least in the EIA forecasts). The results also show room for improvement in policies that have

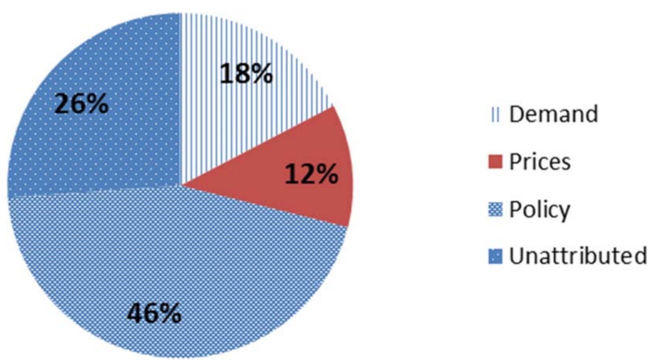


Figure 3. Relative contribution to 2030 GHG emissions decline.

considerable potential for GHG reductions, but have not been ramped up like other policies. For example, there is little room to expand the Renewable Fuels Standard in spite of its contribution to GHG mitigation, given the variation in prices and supplies of renewable fuel feedstocks like corn. However, cost-effective demand-side management policies can be ramped up at the state and federal level that could result in further GHG mitigation while also improving economic outcomes (Nelson *et al.* 2014).

The bottom line is that despite the lack of a coordinated national GHG policy in the US, thanks to market forces and actions at the federal, state, and local levels aimed at enhancing energy security and competitiveness, the likely trajectory of future US GHG emissions has been substantially lowered. GHG emissions can be reduced due to thoughtful policy actions rather than considering that GHG reductions are largely possible only during economic downturns.

Acknowledgements

The authors thank Hillard Huntington at the Stanford Energy Modeling Forum for his helpful review of this analysis, as well as Constantine Boussalis and Travis Coan with the Harvard Law School Empirical Research Services for their review of the econometric analyses presented herein.

Disclosure statement

No potential conflict of interest was reported by the authors.

Supplemental data

Supplemental data for this article can be accessed here.

Funding

This work was partially supported by the Center for Climate Strategies.

Note

1. A Kaya identity regression model based on Raupach *et al.* (2007) was also fitted that used GDP, energy intensity (primary energy demand/GDP), and GHG intensity (GHGs/primary energy supply) to predict GHG emissions. The regression results were not stable due to colinearity (high correlation) between the energy intensity and GDP variables.

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Appendix 1. Descriptive Statistics

Variables (not logged, all prices in $2005)	*N*	Mean	SD	Min	Max
GHGs	120	6185.62	511.26	5425.5	7950.2
GDP	120	17,478.52	3248.7	12,760.45	25,350.96
Industrial shipments/GDP	120	0.45	0.03	0.37	0.51
Crude oil price	120	80.76	22.36	49.64	122.07
Natural gas price	120	5.98	0.95	3.79	8.59
Coal price	120	1.78	0.12	1.58	2.08
Coal supply (%)	120	0.22	0.01	0.19	0.26
Liquid fuels supply (%)	120	0.38	0.01	0.37	0.4
Natural gas supply (%)	120	0.23	0.01	0.2	0.25
Nuclear supply (%)	120	0.08	0.01	0.07	0.09
Renewables supply (%)	120	0.08	0.01	0.06	0.1
Commercial energy demand (%)	120	0.2	0.01	0.18	0.21
Residential energy demand (%)	120	0.21	0.01	0.2	0.23
Transportation energy demand (%)	120	0.28	0.01	0.27	0.3
Coal generation (%)	120	0.48	0.03	0.42	0.57
Renewables generation (%)	120	0.12	0.02	0.08	0.17
Natural gas generation (%)	120	0.2	0.02	0.14	0.24
Nuclear generation (%)	120	0.18	0.01	0.15	0.2
Residential energy intensity (kBTU/ft^2)	120	50.62	4.69	42.1	60.9
Commercial energy intensity (kBTU/ft^2)	120	108.12	4.46	101.11	115.06
Industrial energy intensity (kBTU/$ shipments)	120	3.78	0.38	3.12	4.66
Renewable fuels (%)	120	0.06	0.02	0.02	0.11
Light duty vehicle (MPG)	120	31.88	3.78	26.04	38
Commercial truck (MPG)	120	17.54	1.59	14.9	20.3